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Beyond Image Quality

Failure Analysis from Similarity Surface Techniques

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And founder,

Securics Inc.

With past work by at Lehigh by R. Micheals, Weiliang Li, Yin Chen, Xiang Gao T. Riopkia,

At UCCS with Jay Potharaju

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Recommendations

- Need to develop consistent measure of quality of "utility quality measures" that allow comparison.
  - We recommend FP ROC.
- Community should separate issues different "Qualities" and needs to work on at least 4 different "utility" qualities:
  - Capture, Enrollment, Match/Failure, Share
- Compared to finger matching, Data/features used by face algorithms has significantly greater variations, so cannot expect same "prediction" ability from image quality.
- Blind SNR estimates workable for image-quality. Can be improve by weighting "feature regions" and learning features for Eyes/Glasses/Pose.
- Can develop a general PRAT/FASST Toolkit for algorithm "match quality" from biometric algorithm specific data.

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Blur

Atmosphere/Weather

Noise

How do sensor/world variations impact Face Recognition?

Compression

Gamma

Dynamic Range

Need controlled/designed experiments!

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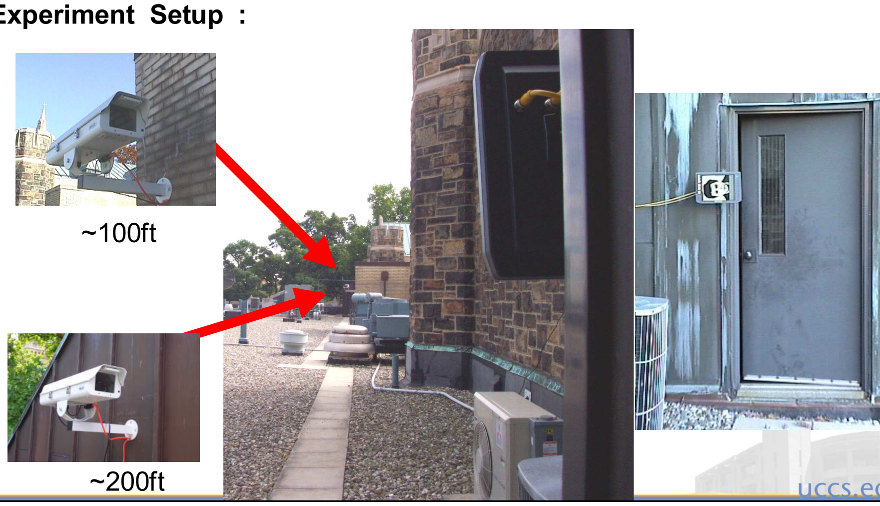
Photo-head Data Acquisition

Sensor : FOV 0.5° and 0.25° imaging (equivalent to 1600mm and 3200mm focal lengths).

Experiment Setup :



~100ft

~200ft

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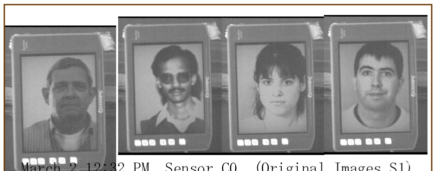
Example Photoheads

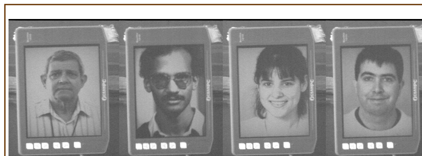
S1 Gallery

S2 Gallery



March 2 12:32 PM, Sensor C0, (Original Images S1)

(C0, S1) Probe Set



March 2 12:32 PM, Sensor C0, (Original Images S2)

(C0, S2) Probe Set

March 2 12:32 PM, Sensor C1, (Original Images S1)

(C1, S1) Probe Set

March 2 12:32 PM, Sensor C1, (Original Images S2)

(C1, S2) Probe Set

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Example "photohead" data

100ft **200ft**

9:30am – 8:pm (4 samples per hour)

DARPA HID Conference, September 2002

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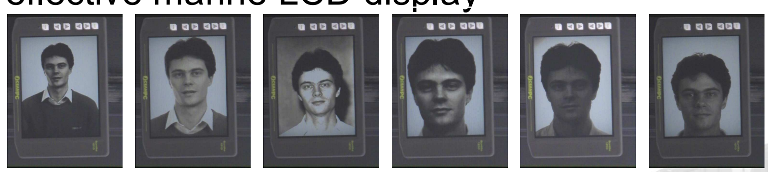
Experiments

- Four datasets: JPEG, Outdoor, Blur, & Gamma
  - **JPEG**: Varying image quality from 100 to 0

  - **Outdoor**: Images collected from outdoor anti-reflective marine LCD display



DARPA HID — HBASE collection: Camera distance = 100 / 200ft

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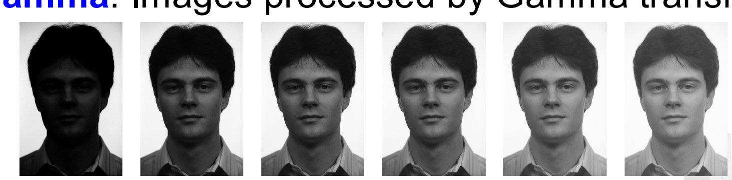
Experiments

  - **Blur**: Blurred images by Gaussian kernel 7×7

  - **Gamma**: Images processed by Gamma transform



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Facial Image Quality from blind SNR estimate

Statistical properties of edge image change with quality. Suppose pdf of edge intensity image, $||\nabla I||$ is $f_{||\nabla I||}(\cdot)$ has mean μ.

Choosing a window around eyes, define Face SNR image quality as

$$Q' = \frac{\sum \text{edge above } 2\mu\text{'s pixels}}{\sum \text{edge pixels}} \simeq \int_{2\mu}^{\infty} f_{||\nabla I||}(r)dr$$

Can also apply spatial weighting to key on eyes/nose.

Adapted from [Zhang-Blum-00].

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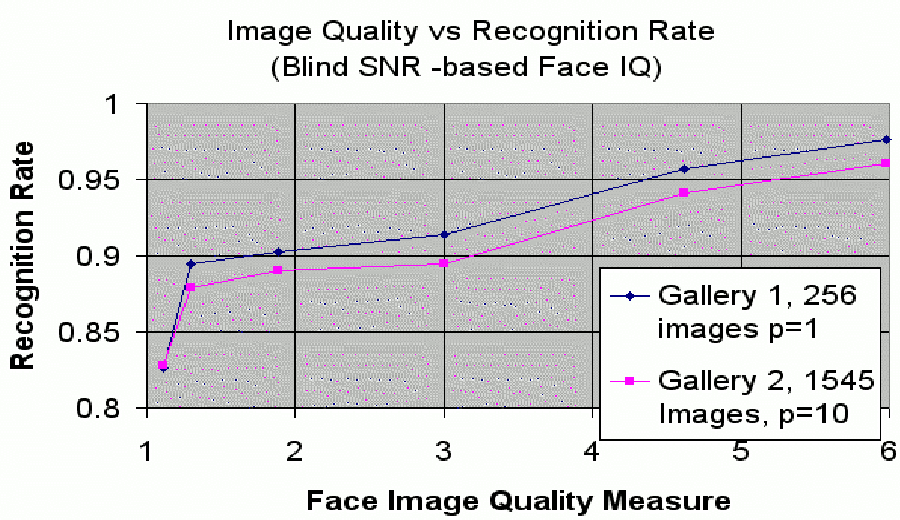

Correlations are .922 and .930 !

Also tried multiple measures of blur and contrast and multi-metric fusion. None were better than Blind SNR estimate.

Tested with FaceIt, PCA, EBGM. Generally report FaceIT

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Why Predict Failure

- System approach – if data is not sufficient can acquire more while subject still available.
- Feedback to improve collection/sensor system.
- Decision Fusion/Boosting – can be used to weight results from multiple algorithms or multiple data sources.
- Help algorithm researchers focus on what needs "fixed"
- For "utility" qualities, task based evaluation is needed providing a "prediction", so can use it for comparison of quality measures

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Approaches

- Input filtering – determining failure before running the classifier:
  - Using image quality to predict failure of face recognition.
- PRAT: Post Recognition Analysis Techniques
  - One example: Failure Analysis from Similarity Surface Techniques (FASST)

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Predicting Recognition System Failure

Recognized
(as GW)

Face Recognition System

Similarity scores

Failure Prediction Engine

Recognition Successful

Recognition Failed

Rejection Successful

Rejection Failed

Rejected
(not in DB)

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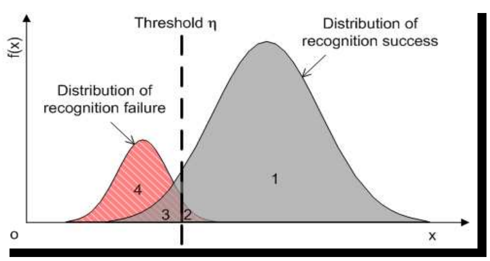
Evaluating Failure Prediction



- Failure Prediction False Alarm Rate

$$FPFAR = \frac{|Case\ 3|}{|Case\ 3| + |Case\ 1|}$$

- Failure Prediction Miss Detection Rate

$$FPMDR = \frac{|Case\ 2|}{|Case\ 2| + |Case\ 4|}$$

	Conventional Explanation	**Prediction**	**Ground Truth**
Case 1	*True Accept*	Success	P
Case 2	*False Accept*	Success	O
Case 3	*False Reject*	Failure	O
Case 4	*True Reject*	Failure	P

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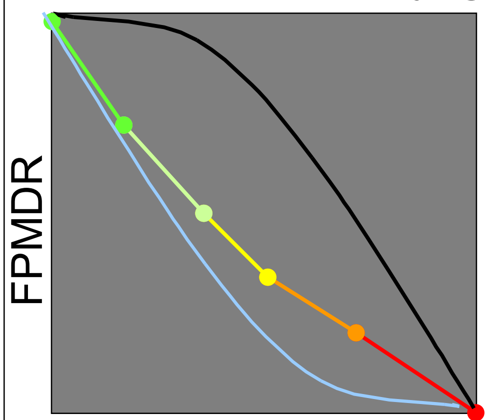
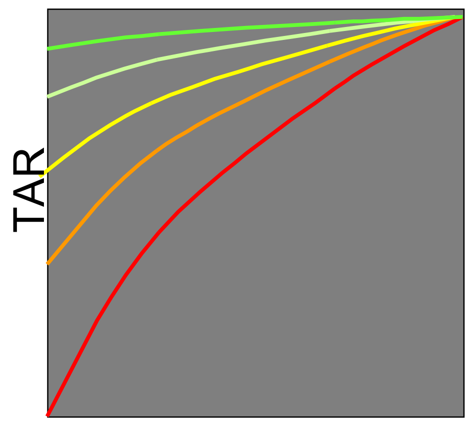
FP ROC Compared to Quality-grouped ROC





FPFAR
Uses Full Data Sets
Vary "quality" threshold

FAR
Segmenting gallery on quality inflates the difference

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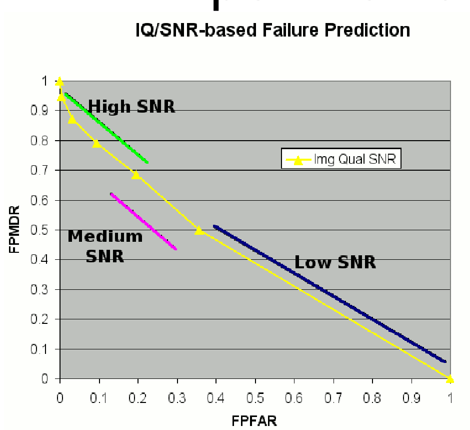
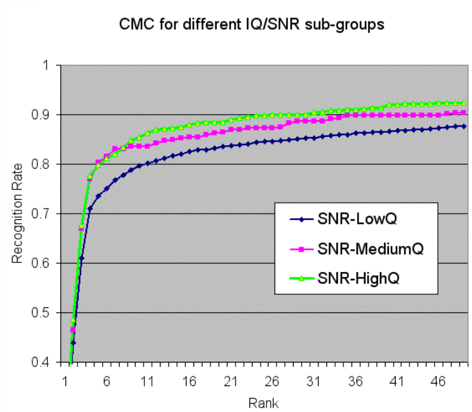
Experimental FPROC vs CMC





Constant HQ Gallery (1024), Group probes by IQ/SNR
12,000 photo-head probes

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FPROC

- ✓ Allows more direct comparison of different quality measures, or a quality measure on different sensors/groups
- ± Requires an "evaluation gallery"
- ± Depends on underlying recognition system's tuning and decision making processes
- – May understate the "impact" of removing poor quality prints from process.

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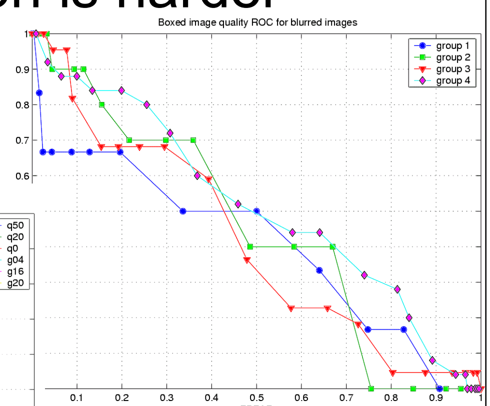
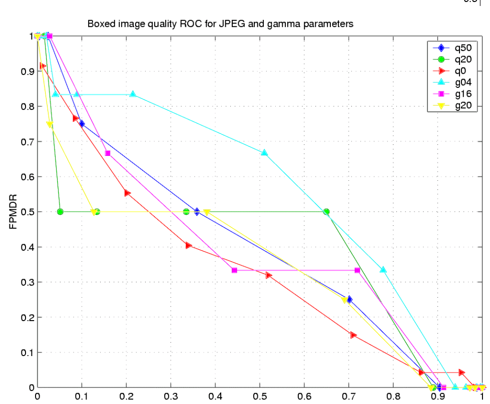
Quality-based Prediction is harder



Jpeg & Gamma



BLUR

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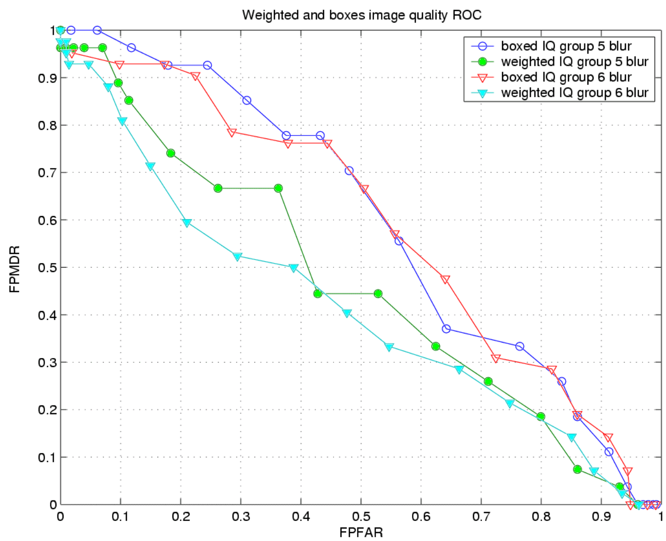
Weighting on “eyes” region helps



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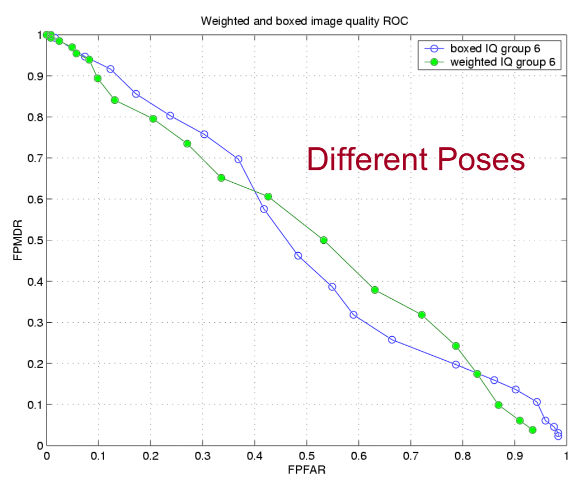
But Probe/Gallery pose differences dominate



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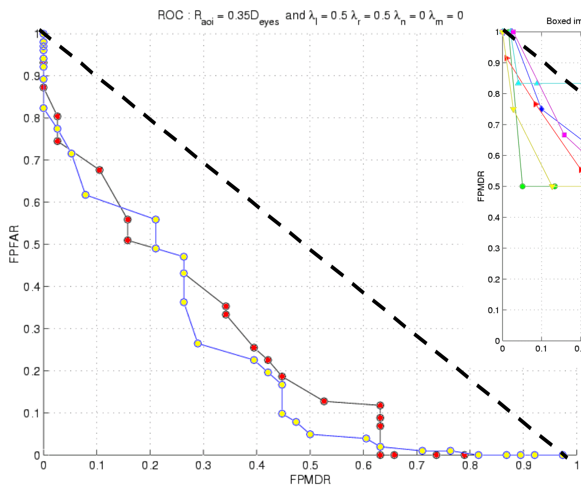
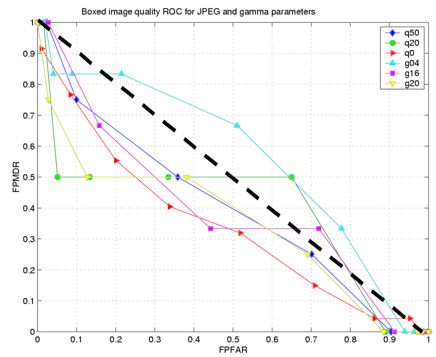
Learning added measures for Facial IQ





Compare to red lin

Add new few Features in Facial IQ based on Ada-boosted wavelets around eyes to "learn" features for eyes closes/glasses.

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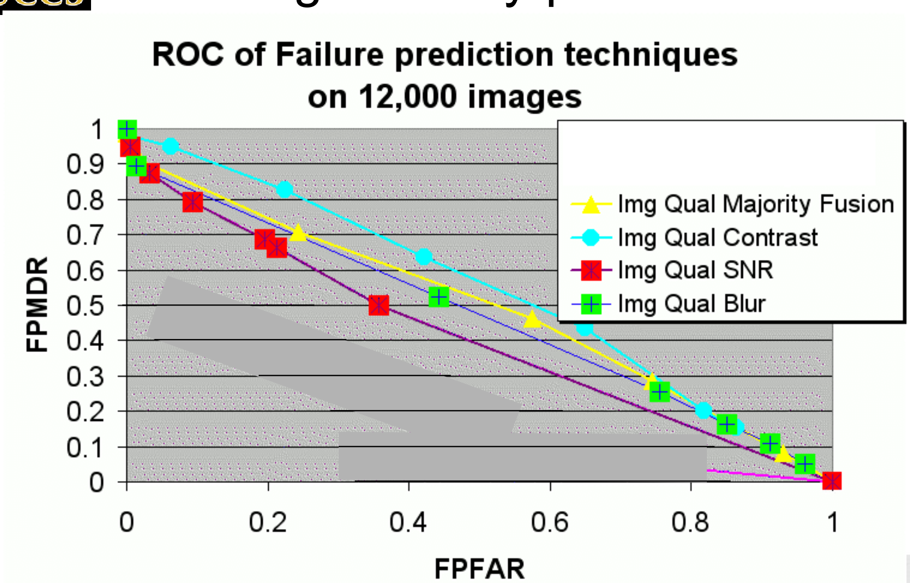
Image Quality-predictions



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FIQ Conclusion

- Statistics of edge intensity distribution (blind image SNR estimate) are well correlated with recognition rates.
- For “good pose/lighing” images the IQ variations are fair predictor of recognition failure.
- Windowing and Weighting help as IQ becomes weak but pose and lighting are more significant.
- IQ not as good predictor when significant pose/lighting/contrast/compression variations are allowed.
- If doing “quality” should include pose/lighting estimates against “standard”

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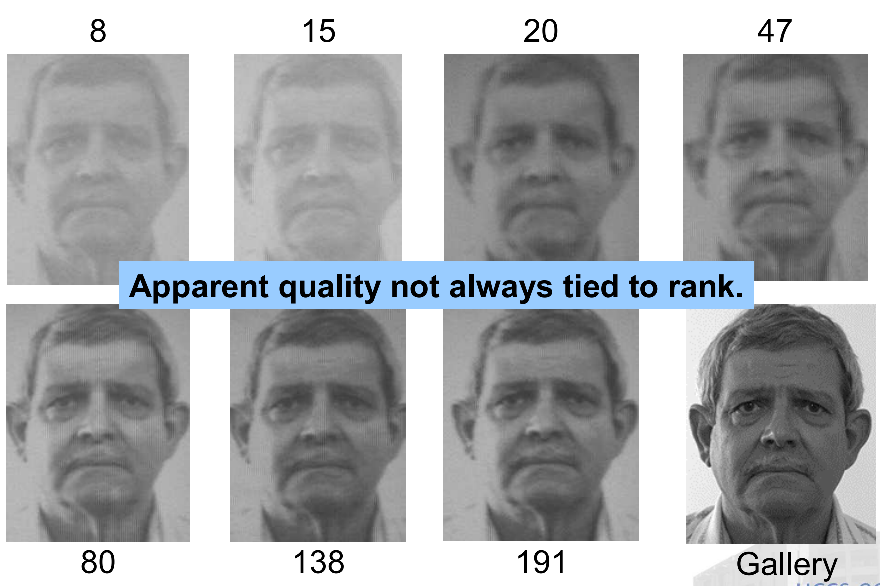
Image quality and rank



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100ft 200ft

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rank: 6 rank: 6

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PRAT: Post-Recognition Analysis Techniques

- Using data from actual recognition process, can Post Analysis predict failure?
- Many Recognition/Classification processes can be viewed using "similarity" scores.
- Failure Analysis from Similarity Surface Techniques. For details see
  - Li-Gao-Boult-05 IEEE Conf. Computational Intelligence for Homeland Security and Personal Safety, 2005
  - Riopka-Boult-05, AVBPA 2005.

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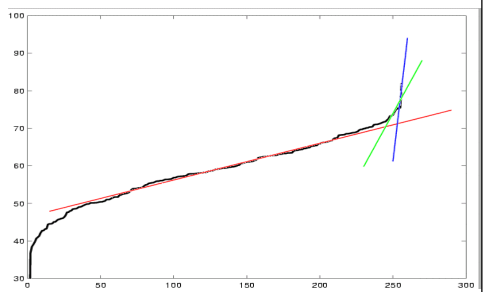
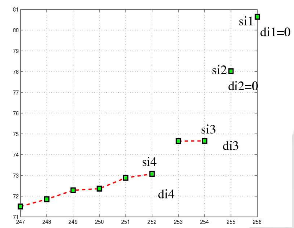
Similarity-based recognition

Failure Analysis from Similarity Surface Theory

- Similarity scores say how well target matches each DB entry.
- Used for all biometric Recognition problems
- Usually largest score is “match”. But is it good enough?
- Overall shape say a lot about if it’s a real match.





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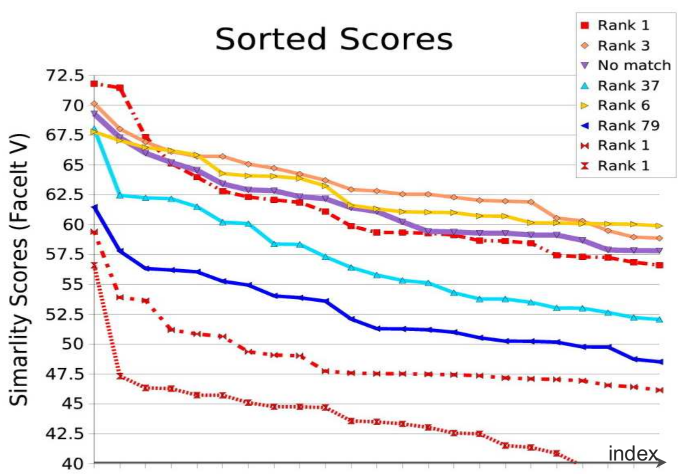
Similarity Score Examples



Sorted similarity scores

$\{s(\mathbf{x}_i, \mathbf{y}_1), s(\mathbf{x}_i, \mathbf{y}_2), \ldots, s(\mathbf{x}_i, \mathbf{y}_n)\}$

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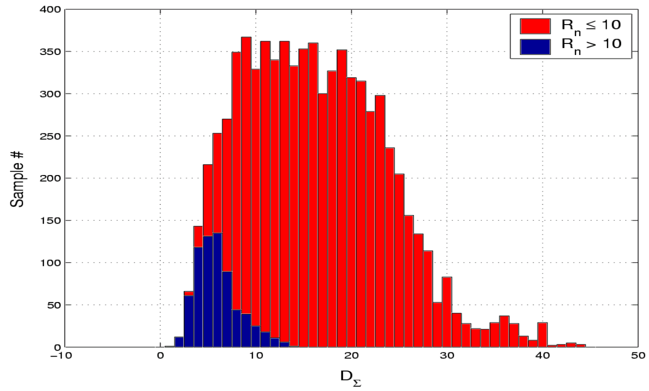
Simple "Slope"

D_Σ = Height difference in similarity score S_1-S_p

Crude Slope estimate = D_Σ / p



- Sample size = 8,423 from *FaceIt*
- Face images from *FERET*

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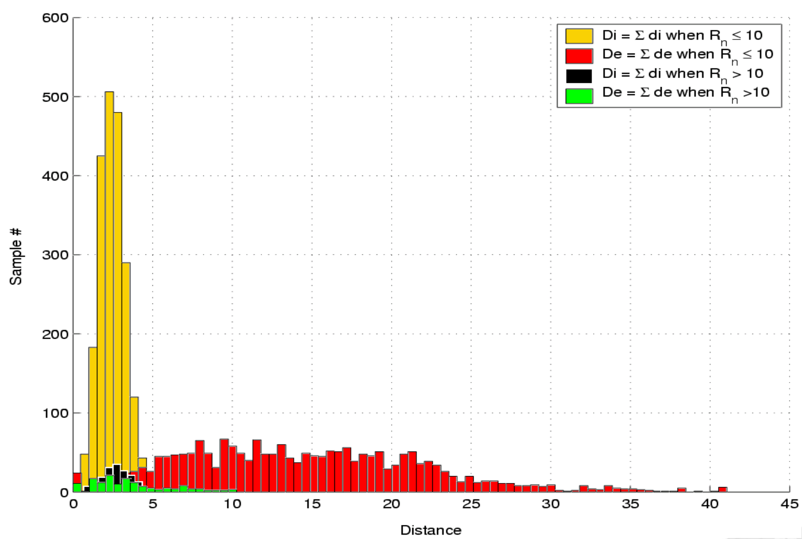
Separation of new Measures



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Forms of FASST tested

- Hand-chosen threshold for "slope" features (common "normalization"?)
- Ada-Boost applied to designed features of sorted similarity data of top 10% (APRAT on slides)
- 3 layer Neural Net applied to top 10% similarity + number of "gallery duplication" count

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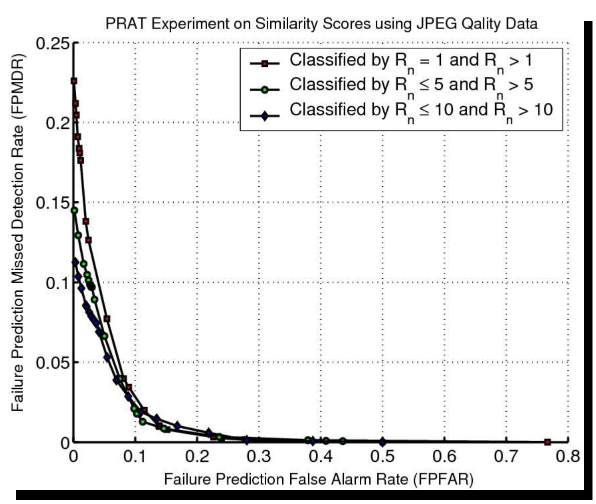
ROC Plots — **JPEG data**



- Sample size = 121,308 × 4
- Three partitions

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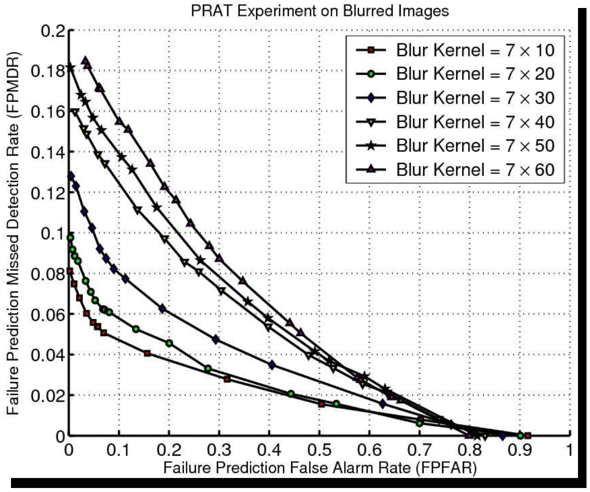
ROC Plots — **Blur data**



- Sample size = 4,064
- Only probe blurred

We find

- ▶ Blur kernel STD ↑ ⇒ performance ↓

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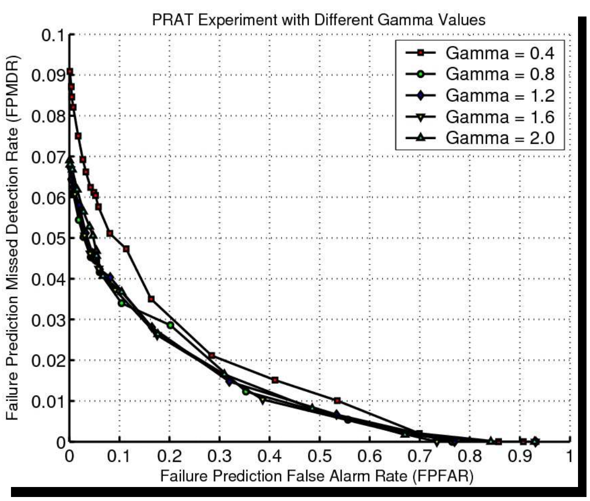
ROC Plots — **Gamma data**



- Sample size = 4,052

We find

- ▶ Gamma transform has little impact on prediction performance

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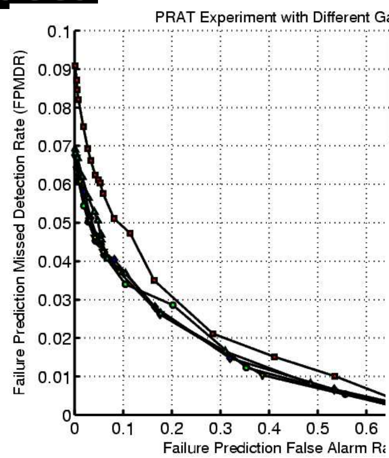
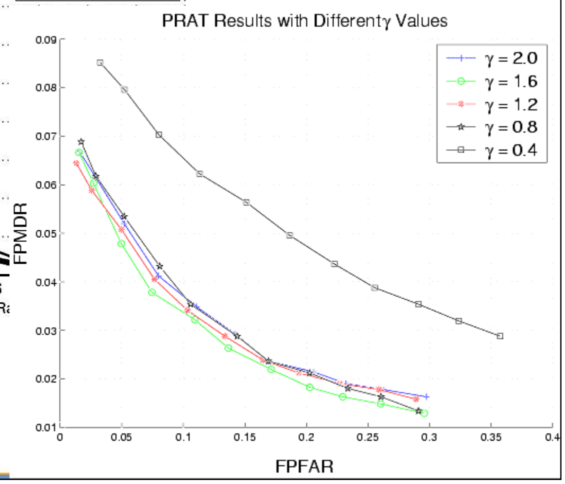
APRAT vs PRAT (Gamma)



APRAT is good and automated!



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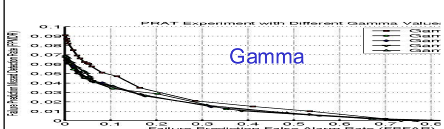
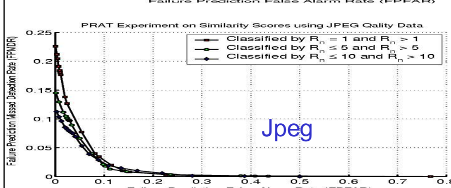
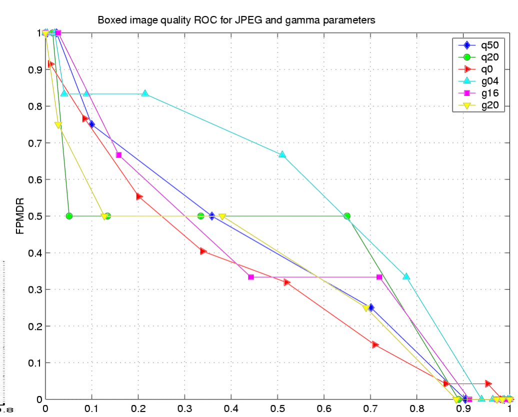
APRAT vs IQ-based prediction

APRAT

(note vertical scale!)







IQ-based

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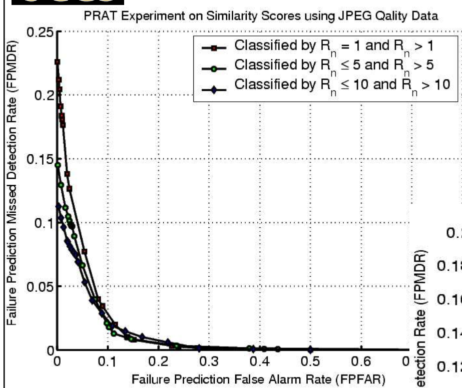
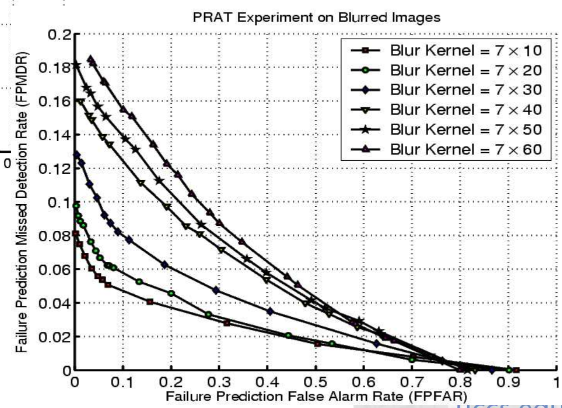
APRAT on JPEG/Blur





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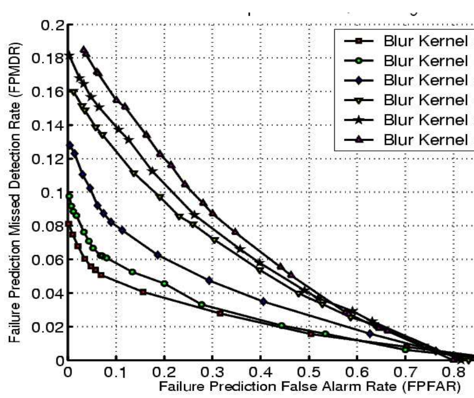
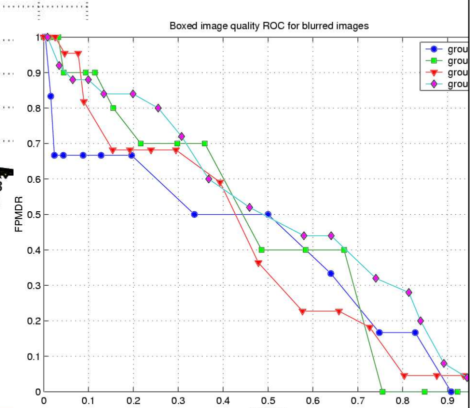
FASST vs IQ Comparison: Blur





(Note vertical scale!)

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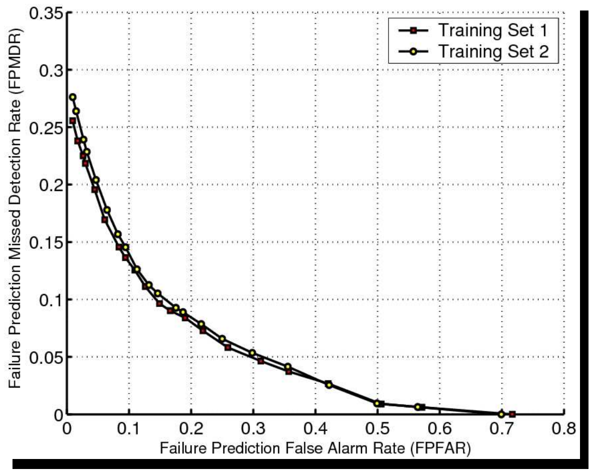
ROC Plots –**Photohead data**



- Sample size = 21,353
- Cross-validation
- Real data (≈)

We find

- Predicting failure in weather more difficult
- *EER (I.e. MD=FA)* is ~12%

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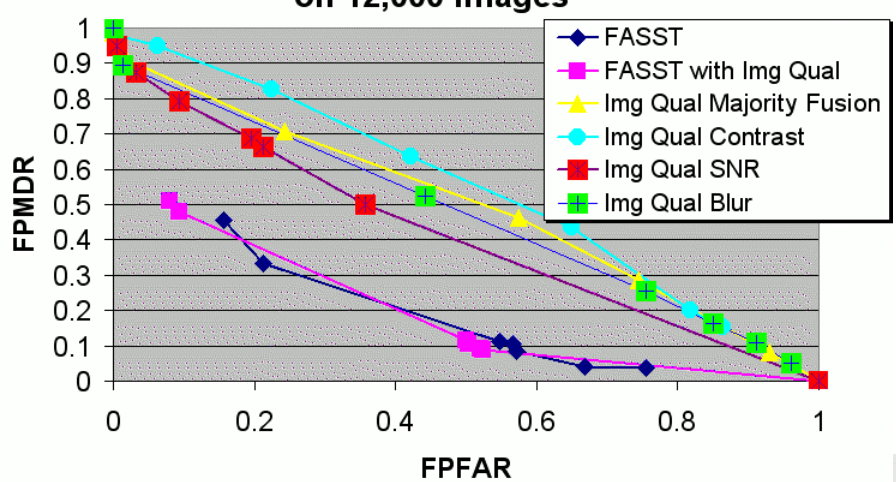
FASST and Image Quality

ROC of Failure prediction techniques on 12,000 images



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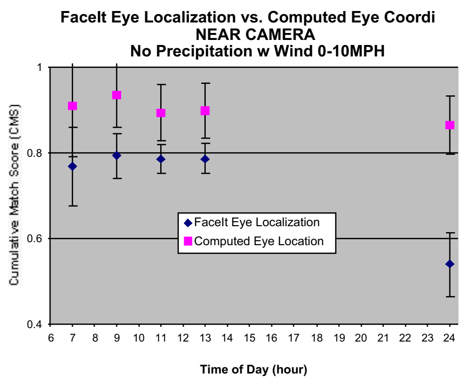
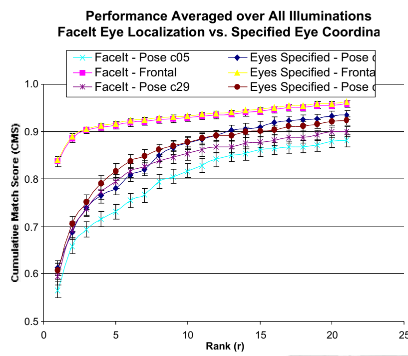
The Eyes Have it

- Recognition Rates unacceptable especially outdoor and at long distances.
- Riopka & Boult in ACM Biometric Workshop showed strong impact of Eye-location.





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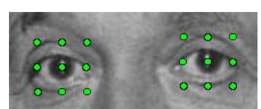
RandomEyes™

Predict when failure likely, and if so perturb location of features and choose best alternative.



Use a Neural Net to predict probable failure from top similarity scores.

Features for prediction:

- Eight Wavelet coefficients from a 4 point discrete Daubechies wavelet transform applied to top 8 sorted similarity scores.
- Each probe had 4 gallery images so we added two other features, number of matching IDs in top 8 and next highest rank of top ranked ID (=9 if none).

- See paper by Riopkia-Boult in AVBPA 2005

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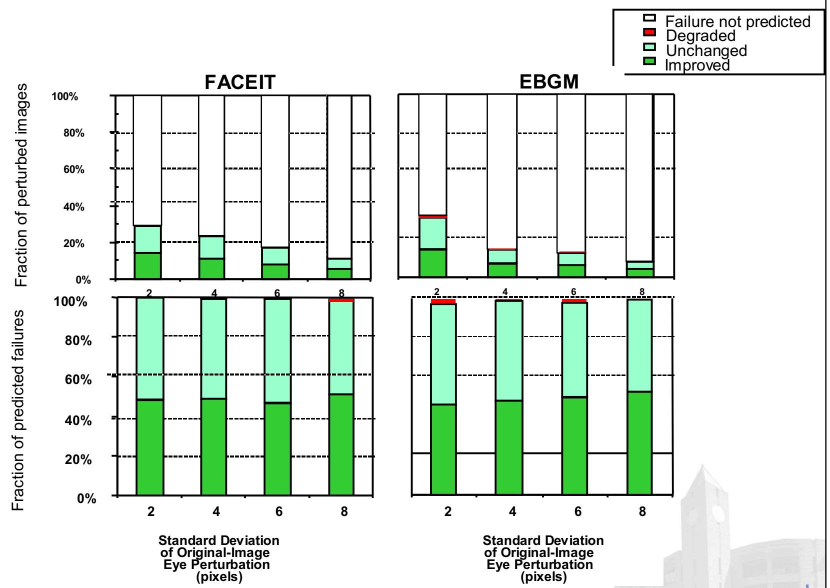
Synthetic Data Results



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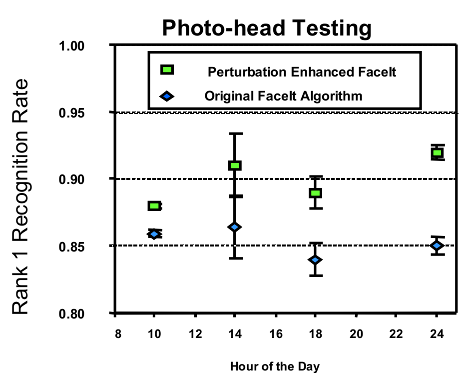
RandomEyes™ helps Photoheads

- Predicting failure and trying perturbations can significantly improve recognition



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Conclusions/Future Work

- IQ strongly correlated to Recognition rate but a weak per image predictor. Not a good predictor when pose/lighting/eye dominates recognition rates.
- FASST, using cumulative intra-cluster distance in high ranking similarity scores is an effective predictor. Two forms on different representations/techniques show its generality.
- FASST + Image quality not significantly better
- FASST + perturbations statistically significantly improve results
- Can we apply FASST on a "test gallery" and make it useful during raw capture?
- Can FASST be useful in factor analysis and experimental assessment?

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Shameless plug

- Workshop on Privacy Research In Vision
- June 2005 (in conjunction with CVPR)
- Discussion oriented workshop but will have papers as well.
  - Papers due Mar 15

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